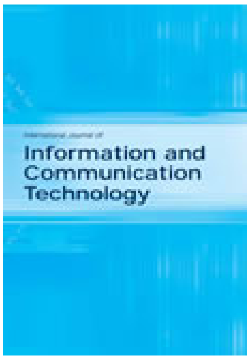

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Analysis of English learning community interaction patterns in social networks based on knowledge graphs

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Abstract: Particularly with regard to language acquisition, the fast expansion of information technology has made social networks a major venue for modern education. Social media give students a virtual space where they may interact, network, and exchange information. English learners support one another, share experiences, and locate fresh materials by means of social media. Still, some students acquire more knowledge or help based on their social network position and connection frequency. This work addresses this problem by analysing English learning community social network interaction patterns with knowledge mapping. This study illustrates learners' social network and knowledge distribution roles using a knowledge graph. This paper also assesses learners' network impact using centrality measures and information flow efficiency. The experimental results show that information diffusion and learning efficacy increase in centred and more involved learners. This study assists to maximise learning strategies and community effectiveness.

Keywords: social networks; knowledge graph; English learning communities; interaction patterns.

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1 Introduction

Particularly in the field of language learning, where social networks offer a virtual environment for students to connect, communicate (Harrison and Thomas, 2009), and exchange knowledge, social networks have become a major venue for modern learning given the fast advancement of information technology. Learners can bypass the geographical restrictions and connect with others worldwide in real time by means of social networks (Bozkurt et al., 2020), therefore augmenting their access to learning materials outside the conventional classroom. This kind of contact gives students more flexible and open approach of learning and breaks the limits of time and distance (Kahu et al., 2014).

Through interactions in social networks, students of English can not only support one another and share their experiences but also get fresh learning materials and knowledge in common debates in the process of learning the language. Through reciprocal cooperation, interactions among students can improve the drive to learn and advance more thorough knowledge of knowledge. Online discussions, sharing of learning experiences or responses to others' enquiries help students to strengthen their understanding of English content, hence fostering a group learning environment (Wu et al., 2017).

Nevertheless, it has been demonstrated that the interaction of social networks not only improves students' motivation but also offers them extra tools and assistance for learning. Through social networks, students may, for instance, exchange their learning experiences, respond to one another's queries, or expand their knowledge of a subject by interacting with other members. Though their position in the social network and the frequency of their connections might enable some students to have access to greater knowledge or assistance, others may be in relative isolation and the consequences of such interactions are not always balanced (Cacioppo et al., 2015).

Knowledge graph, as a structured knowledge representation tool, has been extensively applied in the education sector in recent years (Ji et al., 2021), particularly in analysis of social network interaction patterns and knowledge dissemination channels, therefore displaying significant advantages in order to tackle this problem. Information mapping not only clarifies the links between information points but also shows the interaction between learners and knowledge points, so enabling visualised linkages for in-depth study. Knowledge mapping helps English learning environments to efficiently find the possible links between students and examine their roles in the social network as well as in knowledge distribution (Lee and Segev, 2012). Learners can be given tailored learning recommendations based on the construction and analysis of knowledge graphs in social networks that assist teachers in determining the most engaged learners, significant knowledge nodes and critical channels of information spreading in the society.

Analysing interaction patterns in English learning communities using knowledge graph approaches and social network analysis (SNA) tools is the main aim of this work. This work intends especially to accomplish the following goals:

1. Constructing a knowledge graph-based community model for English learning: Defining nodes (learners, knowledge points) and edges (interactions) in a social network creates a complete graph reflecting learner behaviour and knowledge distribution.
2. Applying social network analytics to assess interaction patterns: Degree centrality, median centrality, and information distribution efficiency help one evaluate learners' interactive activities in social networks and their effect on learning outcomes.
3. Uncovering interactions between learners: Examine the roles of active users in social networks, spot important hubs and channels of information spread, and investigate how interaction patterns affect knowledge sharing.

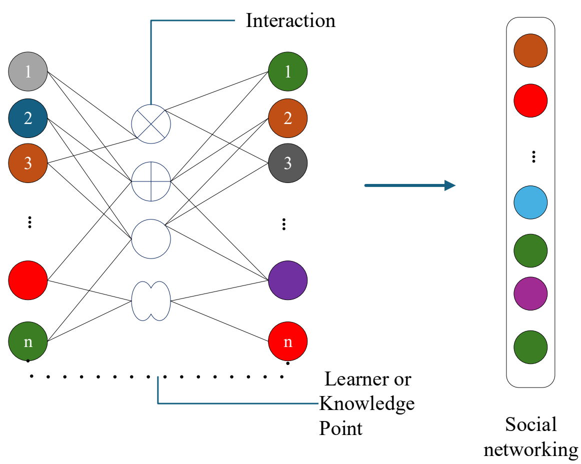
2 Relevant technologies

2.1 Knowledge graph

Widely applied in knowledge management, recommender systems, and other domains, knowledge graph is a method for organised representation of things and their interactions (Wang et al., 2017). In order to expose the interaction patterns among learners and so acquire a better knowledge of the distribution paths and main interaction nodes of knowledge points, in this study we use knowledge graph to analyse English learning communities in social networks. We depict learners, knowledge points and their interactions as a network graph by building a knowledge graph, therefore helping to identify active users, significant knowledge nodes and their propagation linkages in the community.

See Figure 1; node $V = \{v_1, v_2,\ldots,v_n\}$ in the knowledge graph building of English learning community marks learners or knowledge points, and edge $E = \{(v_i, v_j) \mid v_i, v_j \in V\}$ marks interactions.

Figure 1 Knowledge map of the English community (see online version for colours)



The construction process consists in the following phases:

Edge weight computation starts first. Edge weights $w_{i,j}$ are defined to indicate the frequency and strength of interaction between nodes v_i and v_j, therefore quantifying the interaction intensity:

$$w_{i,j} = \alpha \cdot f\left(v_i, v_j\right) + \beta \cdot g\left(v_i, v_j\right) \tag{1}$$

where α and β are weighting parameters; $f(v_i, v_j)$ represents the frequency of interaction between nodes; $g(v_i, v_j)$ indicates the interaction type weight (e.g., query, answer, etc.).

The path of knowledge propagation $P_{i,j}$ length is subsequently defined as:

$$L\left(P_{i,j}\right) = \sum_{(v_k, v_{k+1}) \in P_{i,j}} w_{k,k+1} \tag{2}$$

where $L(P_{i,j})$ represents the shortest path length from v_i to v_j. Knowledge travels more directly the shorter the path length.

Degree centrality follows. Node v_i of Degree Centrality C_D (v_i) measures its interactive activity and helps to find active members of the society (Yustiawan et al., 2015):

$$C_D\left(v_i\right)=\sum_j a_{i,j} \tag{3}$$

$a_{i,j}=1$ if $\left(v_i,v_j\right)\in E$; else, $a_{i,j}=0$.

Betweenness centrality comes just behind this (Brandes, 2001). The betweenness centrality $C_B(v_i)$ of a node v_i gauges its bridging function in the spread of information:

$$C_B\left(v_i\right)=\sum_{s\neq v_i\neq t}\frac{\sigma_{st}\left(v_i\right)}{\sigma_{st}} \tag{4}$$

where σ_{st} represents the number of shortest paths from s to t and σ_{st} (v_i) the count of pathways crossing node v_i. Usually, very meso-centrality nodes are vital for the distribution of information.

Once more, network density exists (Meagher and Rogers, 2004). Indicator of the tightness of interactions, network density D shows the ratio of actual connections between nodes in a community to the theoretical maximum number of connections:

$$D=\frac{2|E|}{n(n-1)} \tag{5}$$

where $|E|$ is the actual number of edges and n is the total number of nodes. The higher the density, the more frequent the interaction of nodes within the network, which is conducive to the rapid dissemination of knowledge.

Node similarity $S(v_i,\ v_j)$ is proposed to evaluate the relationship between learner interests and knowledge points:

$$S\left(v_i,v_j\right)=\frac{\left|K\left(v_i\right)\cap K\left(v_j\right)\right|}{\left|K\left(v_i\right)\cup K\left(v_j\right)\right|} \tag{6}$$

And respectively $K(v_i)$ and $K(v_j)$ are the sets of knowledge points of nodes v_i and v_j. Reflecting an overlap in learning interest or information acquisition, a similarity score near to 1 denotes a great junction of knowledge points between two nodes.

At last, the network has an average propagation efficiency. The knowledge graph's disseminating efficiency E gauges the information diffusion's speed:

$$E=\frac{1}{n(n-1)}\sum_{i\neq j}\frac{1}{L\left(P_{i,j}\right)} \tag{7}$$

A high E-value denotes a tight contact between users and fast spreading of knowledge in the society.

By means of the aforesaid knowledge graph building and analysis, we can quantify the interaction patterns in the community, pinpoint the main knowledge nodes and learners inside the community, and expose the central route of knowledge distribution.

Knowledge graphs play a pivotal role in ELL communities by mapping the intricate network of learner interactions and knowledge dissemination. They offer a visual representation of the connections between learners and the content they engage with, facilitating the identification of key knowledge nodes and influential learners within the community. This structured approach aids in understanding how information spreads and where the focal points of learning activity are concentrated, which is crucial for enhancing educational strategies and community engagement in ELL settings.

2.2 Social network analysis

Widely applied to find learner interaction patterns in communities, SNA is a technique for investigating relationships (edges) between persons (nodes) (Can and Alatas, 2019). SNA clarifies within English learning communities the routes of information distribution, important hubs and community structure among students. Learner conduct can be measured by network analysis to maximise community management and learning tactics.

SNA depends much on the evaluation of node influence. In this regard, the influence propagation model (IPM) is applied to investigate the information flow throughout the network and to evaluate the function of every node in the propagation of information (Molaei et al., 2018). The following model helps to depict information transmission in social networks assuming it is a process based on nodes interacting with each other:

$$S(t+1) = \beta \cdot S(t) \cdot \left(1 - S(t)\right) \tag{8}$$

where β is the propagation rate, hence regulating the speed of information dissemination; $S(t)$ is the influence state of the node at instant t. This formula explains the dynamic information spreading from a node to its adjacent nodes.

A fundamental component of SNA is also propagation path analysis (Ullah et al., 2017). Information is shared in communities via pathways between nodes; the length and weight of the channels define the information transfer's efficiency. Usually stated as the level of interaction between learners, the weight of the shortest path can be set in line with this:

$$P_{ij} = \sum_{k=1}^{n} w_{ik} \cdot w_{kj} \tag{9}$$

where w_{ik} and w_{kj} respectively represent the strength of contact between node k and node j and between node i and node k respectively. Calculating all feasible paths helps one to clearly find the important propagation paths and community nodes.

Furthermore important for exposing the internal network structure in social media is community detection (Lancichinetti and Fortunato, 2019). Community detection helps to identify closely-knit groups of students who are sometimes crucial for the spread of knowledge. Modularity offers a measure of the quality of community segmentation; it is obtained using the following formula:

$$Q = \frac{1}{2m}\sum_{i,j}\left(A_{ij} - \frac{k_i k_j}{2m}\right)\delta\left(c_i, c_j\right) \tag{10}$$

where k_i and k_j are the degrees of nodes i and j respectively; m is the overall number of edges in the network; $\delta(c_i, c_j)$ is the indicator function; 1 if node i and node j belong to the same community, and 0 otherwise. A_{ij} is the element of adjacency matrix indicating whether nodes i and j are connected or not.

By means of community segmentation, one can find the 'core' groupings in a network and the interactions within these groups, therefore exposing the trends of interaction among individual learners in an English learning community. Community detection helps one to maximise the structure of the community and identify which students are vital in the spread of knowledge.

Apart from community segmentation, another important SNA indicator gauges the degree of node propagation strength, thereby determining the contribution of every node to the general information spreading. Calculating the 'propagation potential' of a node can help one to express the strength of node propagation: the formula yields this value.

$$\pi_i = \sum_{j \in N(i)} w_{ij} \cdot C_j \tag{11}$$

where π_i denotes the propagation potential of node i, $N(i)$ is the set of neighbours of node i; w_{ij} is the strength of the interaction between node i and node j; C_j is the centrality – that is, meso-centrality or degree-centrality – of node j. The formula forecasts the contribution of node i to information distribution and gauges its effect on its neighbours.

In SNA, network connectedness is also a crucial statistic at last. The general connectedness between the nodes of a network determines its connectivity. The general structure of the community and the effectiveness of information spreading may be evaluated by computing the average shortest path length L and the clustering coefficient C of the network:

$$L = \frac{1}{n(n-1)}\sum_{i,j \in V} d(i,j) \tag{12}$$

Given n as the total number of nodes and $d(i,j)$ as the shortest path from node i to node j.

Conversely, the clustering coefficient C is computed as the frequency of triangle formation between node neighbours and reflects:

$$C = \frac{3 \cdot \text{number of triangles}}{\text{number of connected triplets}} \tag{13}$$

The information distribution is more effective and the link between groups of students inside the community is closer the greater the cluster coefficient.

By means of these studies, we are able to expose the interaction patterns, information flow channels, and community structure of English learning communities, thereby offering great support for further optimisation of the learning process and community management.

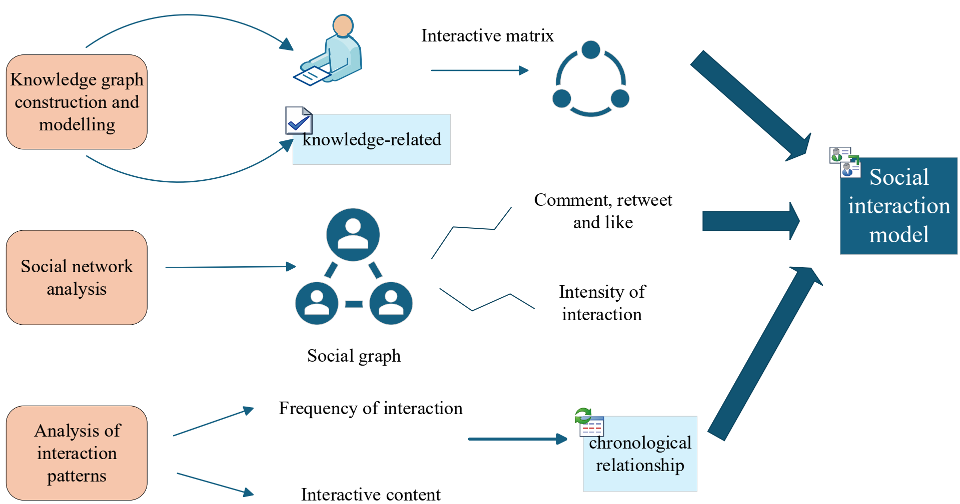
Knowledge graphs provide a structured representation of learners and knowledge points, while SNA reveals the dynamics of interactions and information flow. Together, they offer insights into community engagement and learning efficacy, aiding in the development of strategic educational interventions tailored to the needs of ELL environments.

3 A framework for analysing the interaction patterns of English learning communities in social networks based on knowledge graphs

3.1 Overview of the model

Based on knowledge graphs, we present a paradigm in this chapter to analyse English learning communities' interaction patterns in social networks (see Figure 2).

Figure 2 Model framework (see online version for colours)



Aiming to expose the interaction patterns among learners, the paths of knowledge point dissemination, and the impact of important nodes in the English learning community, the framework combines knowledge graph, SNA and data mining techniques with multi-level modelling and analysis. Combining learners' interaction data with knowledge graphs will help to create a dynamic, multi-dimensional analytic system, thereby guiding the framework. Knowledge graph building module, SNA module, and interaction pattern analysis module makes three primary divisions to the framework. Every module not only exists independently in theory but also depends on each other in data flow and model computation, which together help to enable in-depth study of community interaction patterns.

1 Knowledge graph construction and modelling

Under this paradigm, the knowledge graph construction module aims to gather and organise the links between English learning community knowledge points and learners. Building the correlation between nodes and edges – where nodes stand for learners (user) and knowledge points (knowledge points) and edges for interactions or learning activities between learners and knowledge points – is the essence of this module. First, it is necessary to extract from the social network data the link between every student and its acquired knowledge point. The interaction matrix R can be expressed assuming that the set of knowledge points is $K = \{k_1, k_2, \ldots, k_m\}$ and the set of learners in the social network is $U = \{u_1, u_2, \ldots, u_n\}$ as:

$$R = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1m} \\ r_{21} & r_{22} & \cdots & r_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ r_{n1} & r_{n2} & \cdots & r_{nm} \end{bmatrix} \tag{14}$$

where r_{ij} represents the degree of the interaction between learner u_i and knowledge point k_j (e.g., study duration, count of conversations, etc.). This matrix shows how actively each student participates in several knowledge points in the society. Moreover, we may determine the value of the knowledge points and the impact of learners on them by means of graph theory based algorithms (e.g., PageRank, HITS, etc.).

Following the knowledge graph construction, we can also use graph embedding techniques (e.g., TransE, DistMult, etc.) to low-dimensional vectorise the entities (learners, knowledge points) in the graph so supporting the subsequent prediction of learner behaviour and modelling of knowledge point propagation.

2 SNA module

This module's main goals are to create a social graph amongst students and investigate, depending on graph structure, learner interaction patterns. Learners are represented by the nodes of the social network graph; edges show the interactions among learners (e.g., comments, retweets, likes, etc.). The adjacency matrix A with the following formula helps one to characterise the interaction among every student in the social network with other learners:

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix} \tag{15}$$

where a_{ij} represents the degree of interaction between learner u_i and learner u_j, commonly expressed as the total number of interactions or activities each participated in. We present centrality measures including degree centrality, betweenness centrality, and closeness centrality to evaluate the impact of every student in the network and so better grasp the value of learners in social networks.

3 Interaction pattern analysis

This module aims to investigate the regularity and underlying structure of the interactions among students in social networks, recognise the roles of various learners in the community, and so dig into the interactions between them. Apart from clarifying the flow path of information points in the society, the study of interaction patterns lays a foundation for later tailored learning approaches. In this regard, we present an analysis approach grounded in learner interaction frequency, content, and temporal links.

The frequency of interactions among students directly influences the distribution of knowledge points as well as the strength of the connections among them. We define the interaction f_{ij} between every pair of learners to measure the frequency of interaction:

$$f_{ij} = \frac{C_{ij}}{T_{ij}} \tag{16}$$

where T_{ij} shows the time window in which the interactions between learner u_i and learner u_j during a certain period take place; C_{ij} indicates the amount of interactions – e.g., comments, likes, shares, etc. – between them. For instance, T_{ij} is the length of a week if we take account of the frequency of contacts during one week. This formula helps us to measure the strength of interactions between every pair of students and thereby examine their functions in the spread of knowledge.

The efficiency of learner communication depends much on the affective colouration of interactive materials. By use of sentiment analysis, we can better grasp learners' affective tendencies – that is, either positive, negative, or neutral – during interactions. To this aim, we examined the affective state S_{ij} of every interaction's content using a sentiment score model:

$$S_{ij} = \sum_{k=1}^{n} \text{Sentiment}\left(x_k\right) \cdot w_k \tag{17}$$

In a single interaction message, Sentiment(x_k) is the sentiment score of the k^{th} word; w_k is the weight of the word; n is the total number of words in the message. Calculating the sentiment score for the material of every pair of learner interactions helps us to expose whether there is a trend of good interactions between learners and how such interactions influence the distribution of knowledge points.

Learners' interactions usually have a temporal character, in which their responses or topic-based discussions follow a predetermined chronological sequence. We present a temporal pattern mining technique to examine learners' interactive activities inside a certain time span in order to capture the temporal features of interactions. A Markov chain model helps us to explain the interaction state changes among students:

$$P\left(s_{t+1} = j \middle| s_t = i\right) = \frac{C_{ij}}{C_i} \tag{18}$$

where C_i is the overall number of transfers from state i; $P(s_{t+1} = j \mid s_t = i)$ is the likelihood of moving to state j at moment t; C_{ij} is the number of transfers from state i to state j. This model enables the analysis of whether there is any form of temporal dependency in the interacting behaviour between learners and how this dependence influences the spread of knowledge points.

By means of in-depth study of interaction patterns, we may segment students into several interaction communities. We can group learners using community detection based graph partitioning techniques including graph-based spectral clustering approaches to reach this aim. By means of Eigenvalue decomposition, the spectral clustering method aims to increase the connectedness inside communities and reduce the connectivity between communities. Spectral clustering has an objective function F that one may write as:

$$F = \sum_{i,j} \left(a_{ij} - \frac{k_i k_j}{2m} \right) \delta\left(s_i, s_j\right) \tag{19}$$

where m is the overall number of edges in the graph; k_i and k_j are the degrees of learners u_i and u_j; $\delta(s_i, s_j)$ is a Kronecker delta function denoting whether learners belong to the same community. Through maximising this objective function, community detection can assist in the identification of fundamental interaction nodes in the community and group learners according to comparable interaction patterns.

3.2 Evaluation indicators

1 Engagement

One basic indicator of students' social network activity is engagement (Liu et al., 2017). Usually, higher engagement indicates that students interact often in the community and that knowledge is shared and distributed more effectively.

$$E_u = \frac{\sum_{i=1}^{n} f_{ui}}{n} \tag{20}$$

where E_u is learner u's engagement; f_{ui} is the frequency of her interactions at various time slots; n is the total number of time slots.

2 Information spread efficiency

The speed and extent of the knowledge point diffusion define the efficiency of information distribution. Quick knowledge point distribution in a community guarantees effective interactions and quick access to relevant information for students.

$$\eta = \frac{\text{Number of unique knowledge points propagated}}{\text{Time taken for propagation}} \tag{21}$$

The time needed for dissemination is the whole time needed to finish these disseminations; the number of disseminated knowledge points is the number of unique knowledge points distributed in the community in a certain period of time.

3 Interaction density

Interaction density evaluates the degree of community interaction among the students (Yang et al., 2014). More communication and contact among community members resulting from higher interaction density helps to spread knowledge points.

$$D = \frac{2|E|}{|V|\left(|V|-1\right)} \tag{22}$$

where $|E|$ denotes the social network's edge count; $|V|$ represents the overall count of learner nodes. Learners in a social network's degree of interaction is gauged using this statistic.

4 Experimental results and analyses

4.1 Data sets

This experiment uses a public social network platform's dataset, which comprises of a range of interaction data about English acquisition. Learner activity data in the English learning community mostly makes up the dataset; it includes interactive activities among learners, discussion topics they engage in, and basic facts about community members. The dataset contains the substance of the interactions, timestamps, and the relationship between learners and learning content; it also covers behaviours such comments, likes, and sharing among social network users. From the platform, we gathered tags and subjects connected to English learning and built a knowledge graph including learners, knowledge points, and interaction connections. The dataset is fit for evaluating learners' interaction patterns and knowledge distribution channels since it consists of a significant and ordered volume of data.

Table 1 lists the major characteristics of the dataset together with the description and details of every data point.

Table 1 Dataset statistical information

Data item	*Description*
Learner ID	Unique identifier for each learner
Interaction Type	Types of interaction such as comment, like, share
Interaction Time	The timestamp of when the interaction occurred
Topic Tags	Tags related to the English learning topic
Interaction Content	The content of the comment or post made by the learner
Knowledge Point	Specific English learning topics discussed by learners
Interaction Count	The number of interactions a learner has participated in

We conducted the required pre-processing of the data, including the elimination of noisy data, de-duplication, temporal normalisation and other processes, therefore guaranteeing the validity of the experiment. The remaining valid data were applied for additional graph building and analysis following the elimination of noisy data and duplicates. Every interaction record explicitly marks the learner's relationship with the learning materials, the kind of interaction, etc., therefore allowing the knowledge graph to more faithfully represent the learning interactions inside the community.

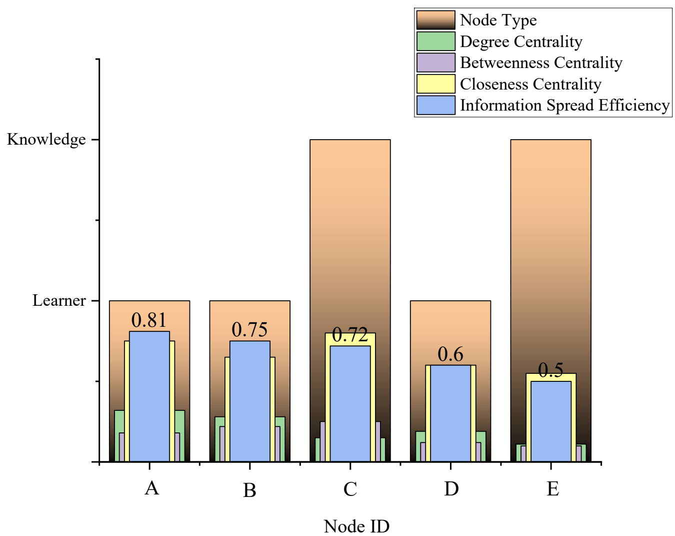
4.2 Experimental procedure

We developed two tests to better grasp learners' interaction patterns in social networks and their influence on knowledge spreading efficiency.

In the first experiment, we build a knowledge graph depending on social network interactions to investigate the interaction patterns in English learning environments. This experiment aims to evaluate using knowledge graph construction and centrality analysis the interaction patterns and the impact of information distribution in social network English learning communities. Analysing the interactions between learners and knowledge points helps us to identify the key knowledge points in the society and their spreading consequences on social networks.

Initially, we built a knowledge graph between learners and knowledge points by gathering interaction data – e.g., comments, likes, shares, etc. – in social networks. Learners and knowledge points are nodes in this graph; interaction activities operate as edges between the nodes. We next computed the degree centrality, median centrality, and proximity centrality of every node and examined their significance within the community. We thus presented the metric of information distribution efficiency to measure the impact of knowledge spreading in the society. Figure 3 exhibits the experimental results.

Figure 3 Experimental results of the community interaction model (see online version for colours)

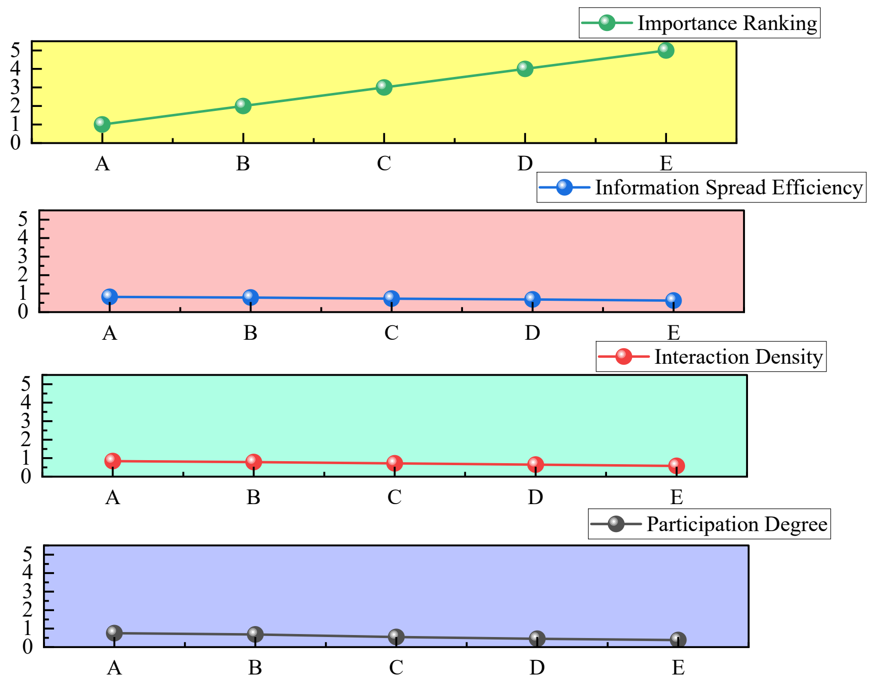


Learners A and B are active nodes in the social network, according to the experimental data, which also exhibit high degree centrality indicating greater interactions with other learners and knowledge point participation in a great number of community exchanges. Learner B particularly shows a high degree of centrality, which indicates its intermediary function in the network and helps to efficiently link several learners and knowledge points and enable the information flow. With the maximum proximity centrality, knowledge point C denotes the primary node of information flow in the society and can rapidly affect the learning behaviour of other nodes. Furthermore, the results of information distribution efficiency indicate that learner A performs the best in knowledge distribution with a dissemination efficiency of 0.81, therefore suggesting that it is a significant information source on the social network. Knowledge Point E has a low dissemination effectiveness of 0.50, which indicates that it has a poor dissemination influence and requires more contact to be generally distributed in the society.

We investigated in the second experiment the interactions between learner involvement, information distribution efficiency in social networks and interaction density. By means of various degrees of social network structure and interaction density, this experiment investigates how these elements influence the knowledge spreading route and the quality of community interactions.

First, we computed every student's social network engagement – a gauge of his or her activity level. Engagement was specifically gauged in relation to the ratio of interactions a student experienced to the highest possible interaction count. We next computed the social network's interaction density in order to investigate the correlation between interaction density and information distribution efficiency and to grasp the degree of interaction amongst learners. At last, we evaluated students' knowledge distribution performance using an information dissemination efficiency indicator, which captures their capacity to share knowledge from themselves to other members. Figure 4 exhibits the experimental results:

Figure 4 Experimental results of SNA (see online version for colours)



From the experimental results, the learner's involvement and the interaction density in the social network directly influence the information spreading efficiency. Learner A is the primary node of information distribution in the social network since it has the highest interaction density (0.85) and engagement (0.75), hence displaying efficiency of 0.82. On the other hand, learner E has the lowest engagement and interaction density and its information distribution efficiency is also the lowest at 0.62, which implies that lower engagement and interaction density can restrict knowledge dissemination and communication efficiency in social networks.

This association validates even more the close connection between the effectiveness of knowledge spreading and the interaction patterns of social networks. The experimental results imply that raising the degree of learners' engagement in social networks not only improves their knowledge distribution but also helps the learning efficiency of the society at general. Thus, maximising learners' involvement and contact density in social networks can considerably increase the speed and efficiency of information transfer, so improving community interaction patterns and learning effectiveness.

By means of these two studies, we acquired a better knowledge of the broad influence of learners' interactive actions on knowledge transfer in social networks. This offers a necessary theoretical framework and pragmatic guide for creating effective social learning environments.

5 Conclusions

This paper reveals the relationship networks and knowledge distribution channels among learners by means of knowledge graph and SNA approaches, so exploring the interaction patterns in English learning communities. This paper not only thoroughly investigates learners' behaviours in interactions but also evaluates the roles and positions of various learners in the community and their influence on the efficiency of knowledge dissemination using SNA approaches by building a social network model based on knowledge graph.

There are still certain restrictions even if this study offers a detailed examination of interaction patterns in English learning environments. First of all, the dataset in this work mostly consists of unique learning communities, thus the sample has limited representativeness and might not be able to fairly depict the interacting behaviours of various kinds of students. Second, despite neglecting elements including learners' personality qualities and social background, which may have a significant influence on interaction patterns and learning results, this study focusses on analyses of learners' location and interaction frequency in social networks. Ultimately, even if the models and analytical approaches suggested in this work offer fresh perspectives for the investigation of community interaction, their generalisability and application still have to be confirmed.

Future research can be further expanded and deepened in the following directions:

1 Diversified data sources: To increase the variety and scope of the data to so enhance the universality of the research findings, we might think about gathering data from other learning platforms and social networks.

2 Personalisation analysis: Thorough investigation of the function of learners' personality traits, learning habits and other elements in social network interactions, and merging with big data analytic technologies to offer learners tailored learning recommendations.

3 Dynamic analysis: While time-series data analysis can be included to investigate the changes in learners' interaction patterns over time and the long-term influence of such changes on learning effects, present research concentrates on stationary SNA.

4 Interdisciplinary integration: Combining ideas from psychology, education, and other fields, the link between social network interaction patterns and elements including learner psychology and motivation can be investigated further to offer more complete educational theoretical support.

By means of these enhancements, future studies will support the optimisation of learner interaction patterns and the improvement of educational impacts, so augmenting the application value of social networks in education.

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